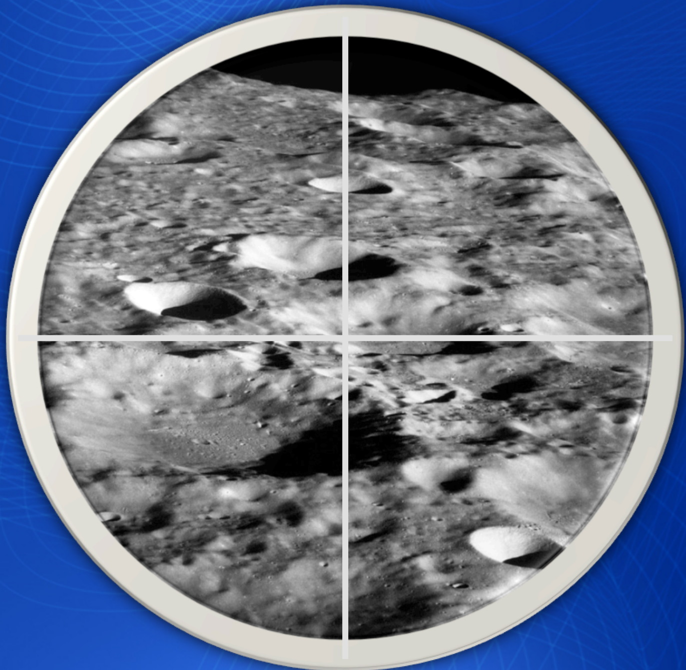
Camera-Aided Inertial Navigation for Pinpoint Planetary Landing on Rugged Terrains



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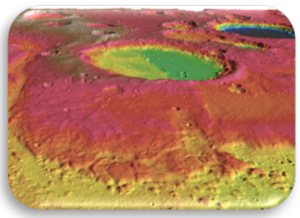
IPPW 8 – Thursday June 9, 2011 – Portsmouth, VA, USA

Motivation

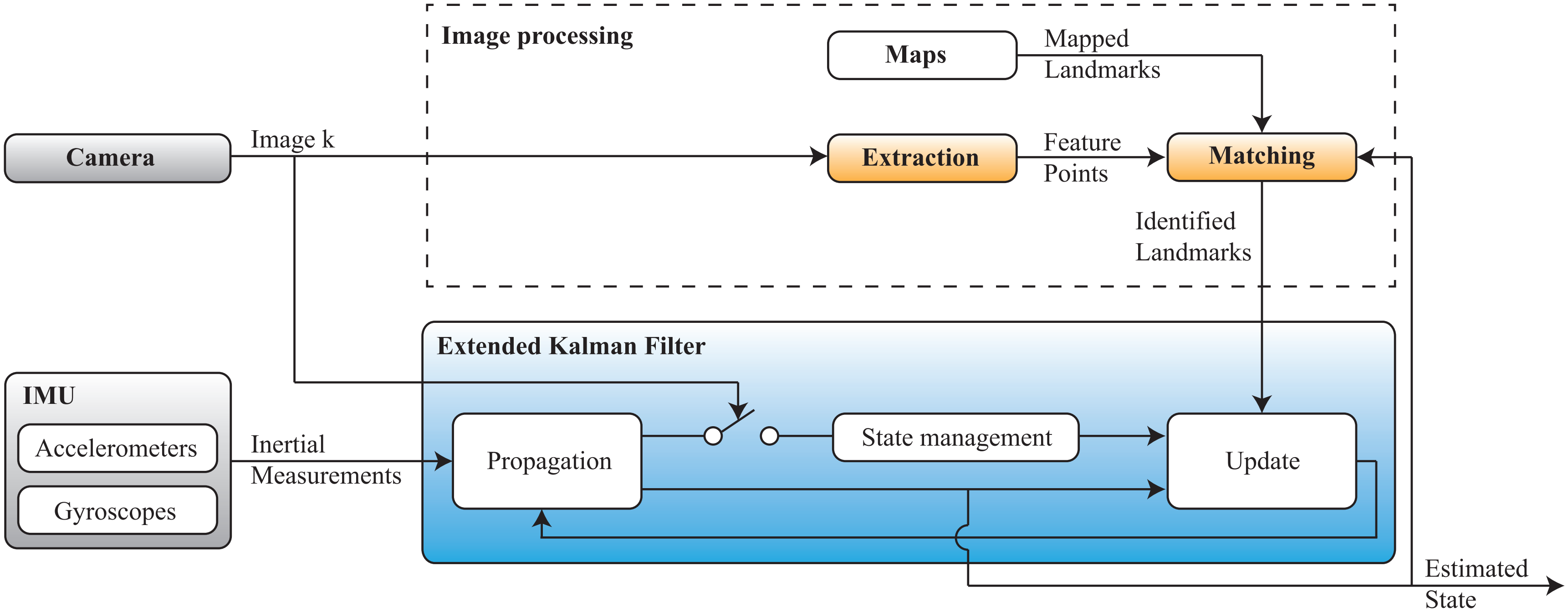


- Planetary landing mission needs:
  - Autonomy
    - Robust to communication link failures and no delays
  - Accuracy
    - Sites of scientific interest
    - Previously-landed assets: rover, astronauts, etc.
    - Technical requirements about the area: illumination patterns, hazard presence, etc.
- On-board terrain sensor: optical camera
  - ✓ Lightweight, cheap, high TRL, passive (works from any distance)
  - X Needs illumination: OK for most landing missions
  - X 2D-only image measurements:
    - Many terrains are highly 3D near the ground (or even farther: asteroids)
- New orbital maps are very accurate (1m-resolution on LRO)
  - Low-altitude absolute planetary navigation can increase accuracy!

Objective: Vision-based pinpoint landing navigation

- **Rugged-terrain capability**
- **Low-altitude operations capability**

System Overview



- Initial position and estimate from previous phase
- Motion propagation with an Inertial Measurement Unit (IMU)
  - Measures non-gravitational accelerations and angular rates
  - ✓ High-frequency estimation, continuous navigation when camera fails
- Matching of online image features with mapped landmarks
  - ✓ IMU biases estimated and error drift is corrected

Summary

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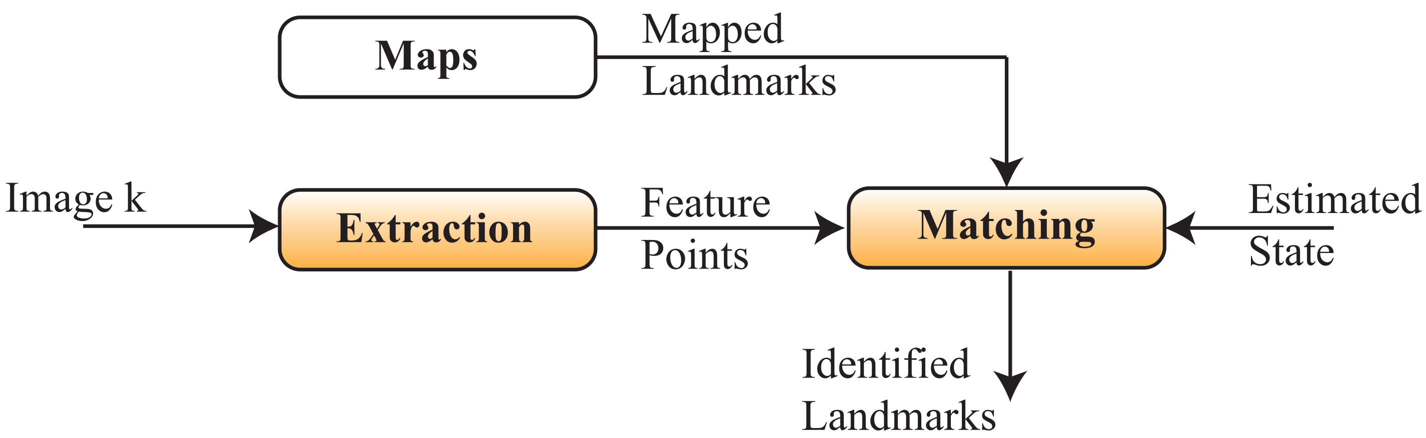
State Of The Art



- Landmark **radiometric** signature (image patch, SIFT/SURF,…):
  - X Illumination-sensitive

- Landmark **geometric** description:
  - •Craters conic-invariant: only for crater landmarks
  - •Landmark projection and nearest-neighbor matching: many outliers
  - •Neighborhood description in rectified terrain plane: flat terrain assumption

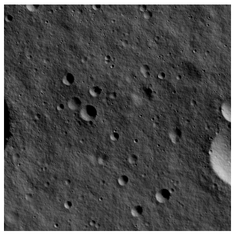
➔ **Goal: 3D-robust geometric method using non-specific landmarks**

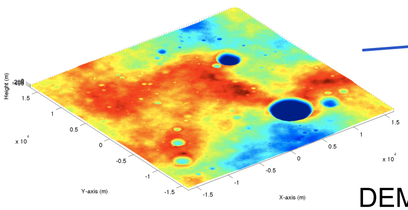
Proposal

- **Proposal:**
  1. **Online extraction** of Harris feature points in the current descent image
  2. **Projection** of the 3D map points onto the image plane estimated in the filter
  3. **Putative matching** based on neighborhood geometry (2 methods)
     a. Shape Context description
     b. Generalized Hough Transform
  4. **Outliers removal** using RANSAC

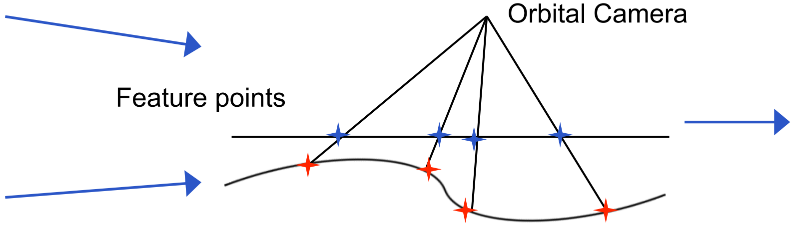
- On-board map generation (prior to the mission):

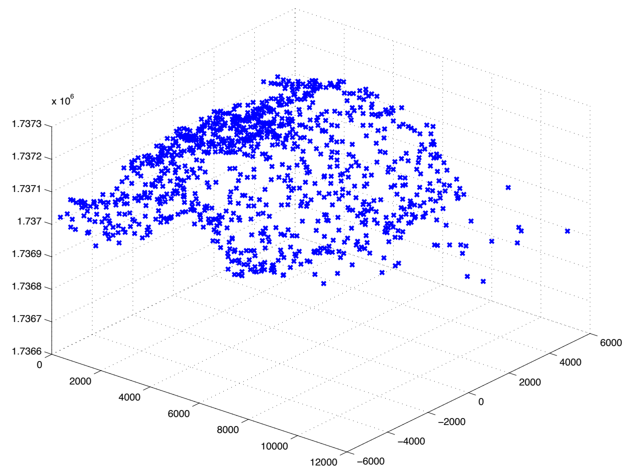
Orbital image





DEM





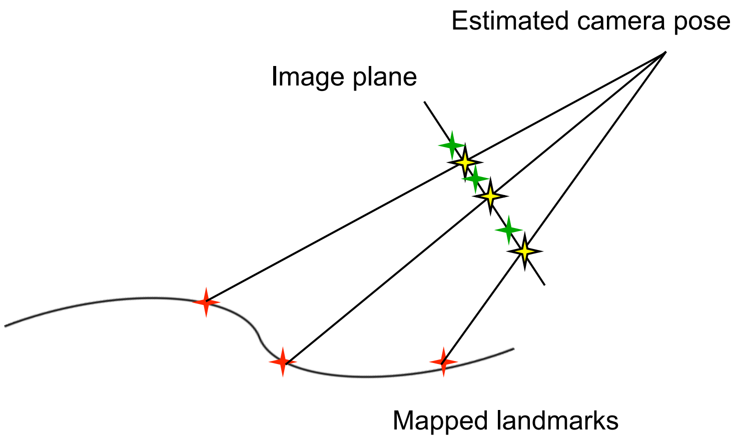
3D points: on-board map

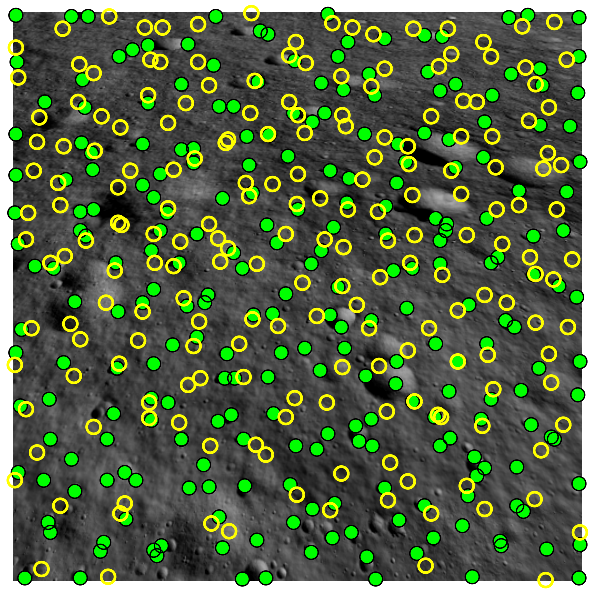
Online extraction and projection

- **Step 1**: Online image feature extraction
  - Harris corner detector

- **Step 2**: Orbital landmark projection
  - On-board map
  - Current camera pose estimated from the filter
  - Known camera calibration model

  ➔ No flat world hypothesis!

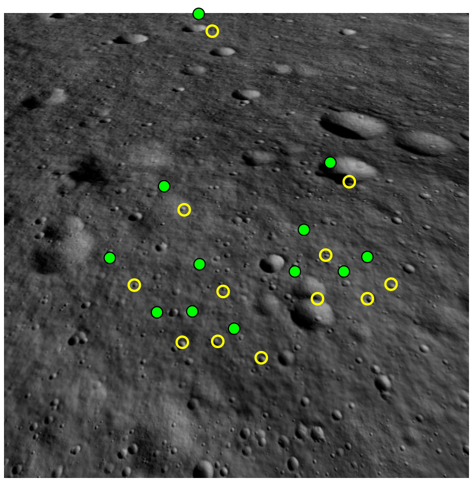


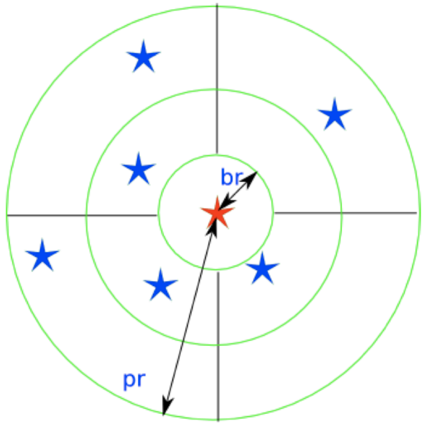


Putative Matching 1: Shape Context

- Shape Context Signature
  - Feature point characterized by the geometric distribution of its neighbours
    - Minimum and maximum distances: b_r and p_r
    - Distance and polar angle
    - Histogram signatures counting neighbours in each quadrant
  - One-to-one signature comparison
    - Distance criterion based on χ^2 distance
    - Selection cut for distances lower than a threshold

➔ Set of promising matches:





Shape context signature (Pham et al., 2009)

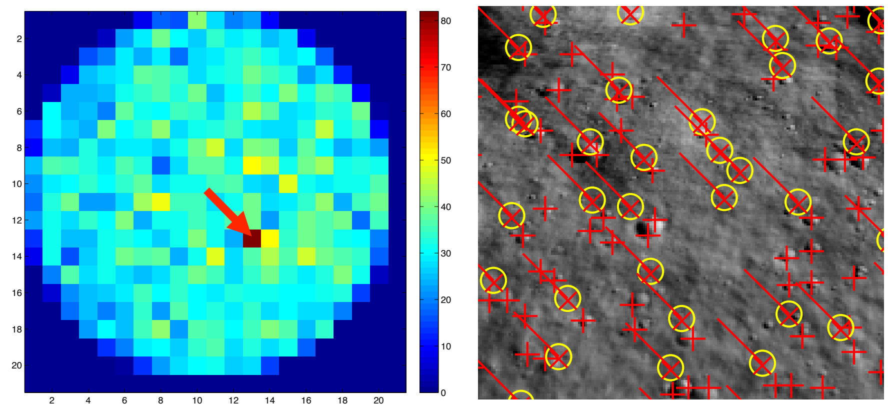
Putative matching 2: Generalized Hough Transform

- **Principle:** Find the best global 2D translation between online features and projected landmarks.

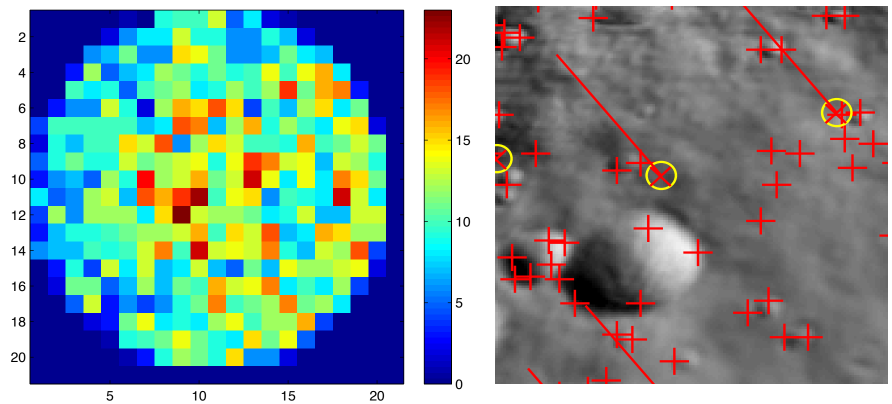
1. Each possible match between an online feature and a projected orbital match defines a possible 2D translation
2. Accumulate all translations
   a. whose norms are below a threshold related to the estimated camera pose covariance
   b. after quantization with a step related to the expected perspective distortion effects
3. Select the peak of the accumulator: it yields the estimated discrete translation
4. Shift the projected landmarks according to the estimated translation and match them with the closest descent point

➔ Accept the match if the closest point is not too far

Successful accumulation



Ambiguous accumulator: not enough landmarks



Outliers removal using RANSAC

- RANSAC: RANdom SAmple Consensus (Fischler et al., 1981)
  - Outliers removal by fitting a model to experimental data
- Model: calibrated camera pose (Fischler et al., 1981)
  - Closed-form solution from 3 matches
  - 4 possible solutions: that closest to the filter estimate is selected
  - Full 3D-terrain capability
- Algorithm
  - Inputs: (2D,3D) putative matches

1. Select a random set s of 3 potential matches
2. Compute the associated camera solution
3. Determine the associated inliers
4. If # {inliers} is larger than the previous maximum, store the inlier vector
5. Back to step 1 until max. number of iterations is reached

  - Outputs: (2D,3D) robust matches
    - Camera model having most inliers
    - **Corresponding inliers ➔ Fed to the filter**

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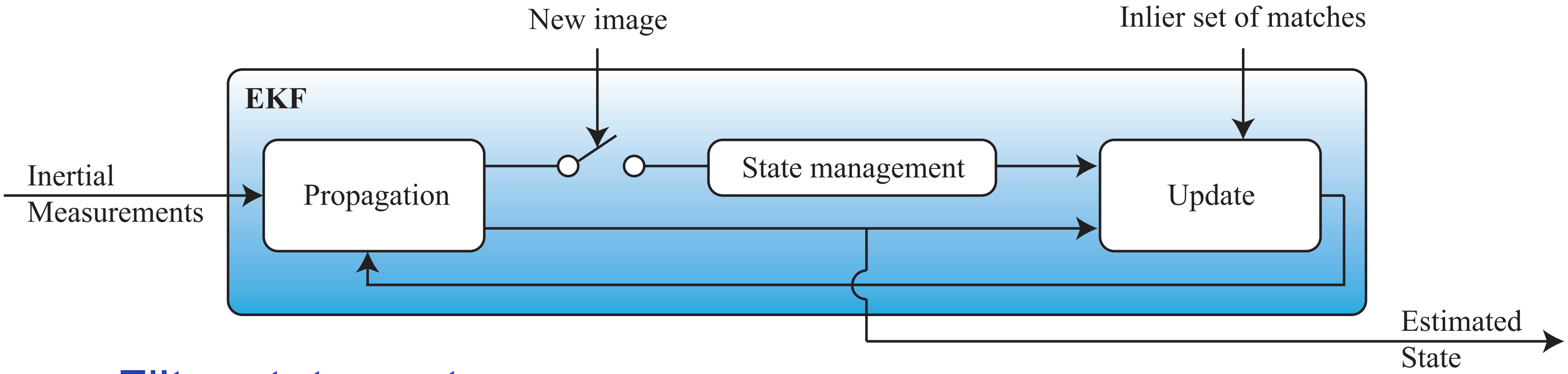
Extended Kalman Filter



- Filter state vector:
  - Vehicle state
    - Attitude quaternion, velocity and position vector
    - IMU (gyroscope and accelerometer) biases
  - Previous camera poses (through state management)
    - Attitude quaternion and position of the camera

  ➔ Allows to account for processing delays through state intercorrelation.

- System model propagation: inertial navigation
- Measurement model: landmark image projection
    - z_j : normalized image coordinates
    - p^c_{clj} : 3D coordinates
    - n_j: noise

$$\mathbf{z}_j = h_j(\mathbf{x}) + \mathbf{n_j} = \frac{\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \mathbf{p}^c_{cl_j}}{\begin{bmatrix} 0 & 0 & 1 \end{bmatrix} \mathbf{p}^c_{cl_j}} + \mathbf{n_j}$$

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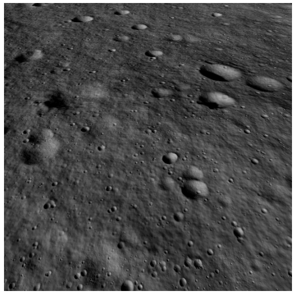
Simulation environment

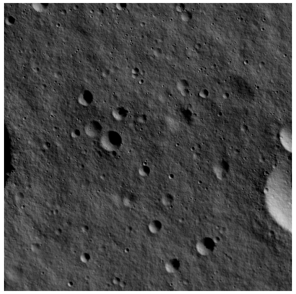
- Test Trajectory selected: Moonlanding approach phase
  - Duration: 80 seconds, 2-km altitude and 65 m/s velocity at startup
  - Guidance is based on that of Apollo LM

- Matlab Simulink IMU model calibrated to match performances of state-of-the-art space IMUs.

- Virtual terrain generated on PANGU
  - Lunar-like DEMs
  - Descent images generation
    - Focal plane placed using true pose from simulator.
    - 512X512 8-bit image spanning 70 deg FoV
    - Gaussian noise: m=0, σ_{im} = 1 intensity level
  - LRO-like orbital images
    - 2.5 deg FoV, 50 km-altitude, 2048x2048 pixels, 8 bits
    - 20° azimuth illumination difference with descent sequence

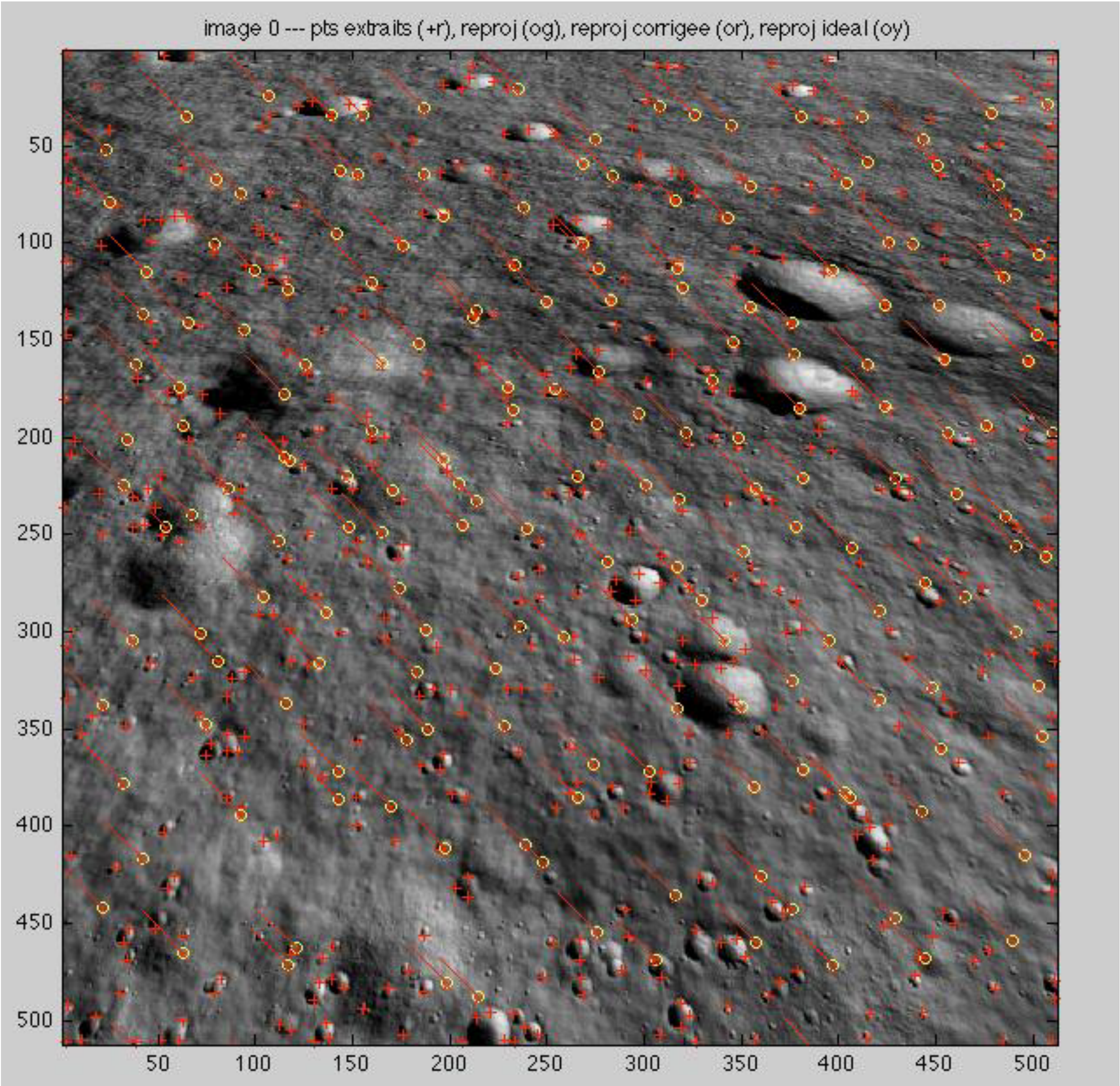


Online descent image



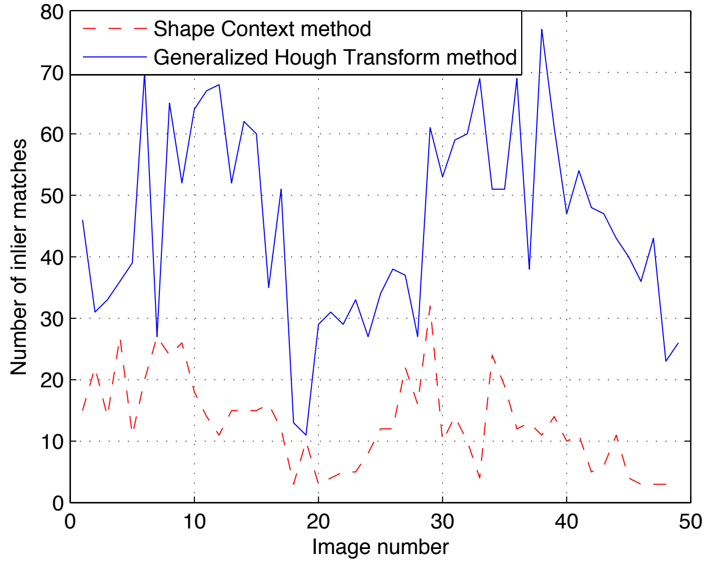
Orbital image

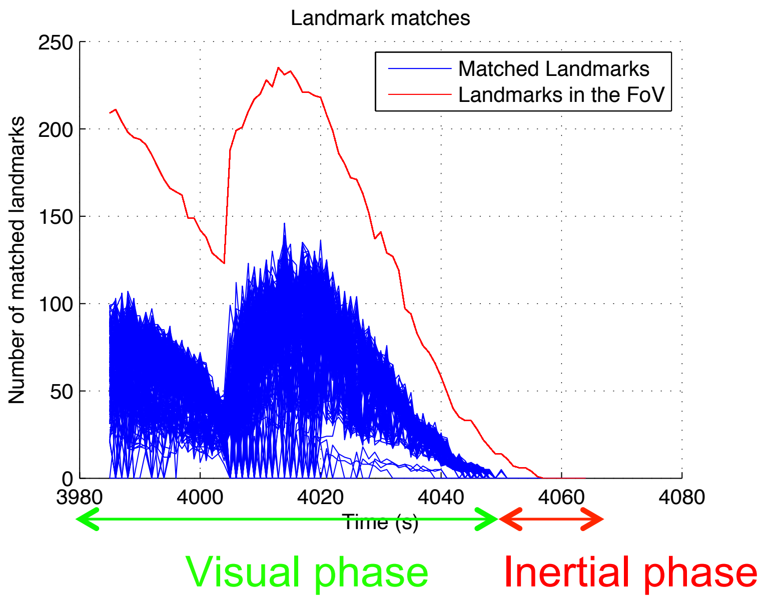
Descent sequence



Matching performance comparison

- Shape Context vs. Generalized Hough Transform (GHT):
  - Each is tuned empirically for best performance
  - GHT matches more landmarks
  - Matches are spread more widely in the image
    - ➔ More useful measurements for the filter

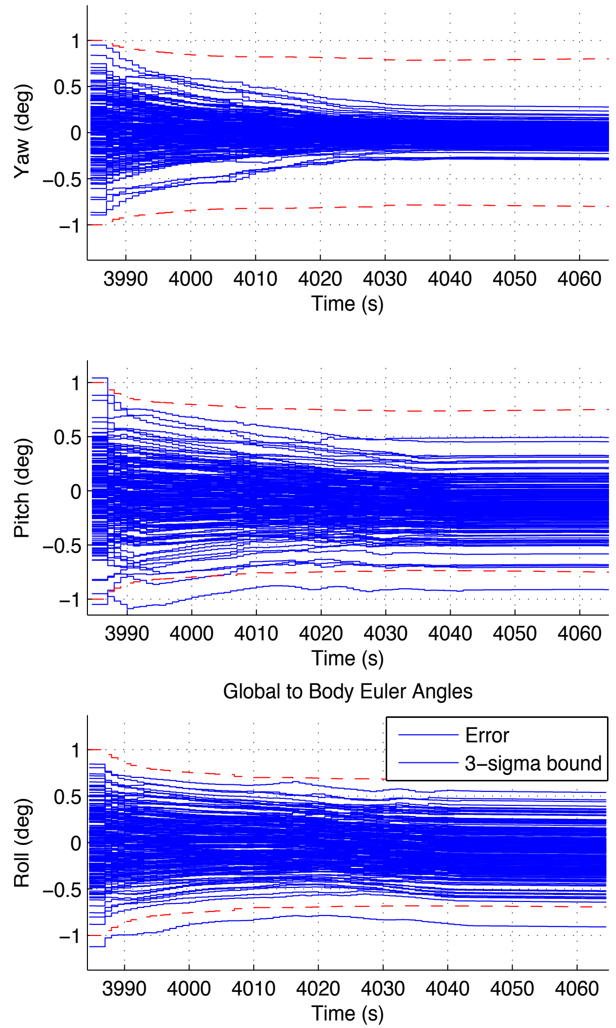




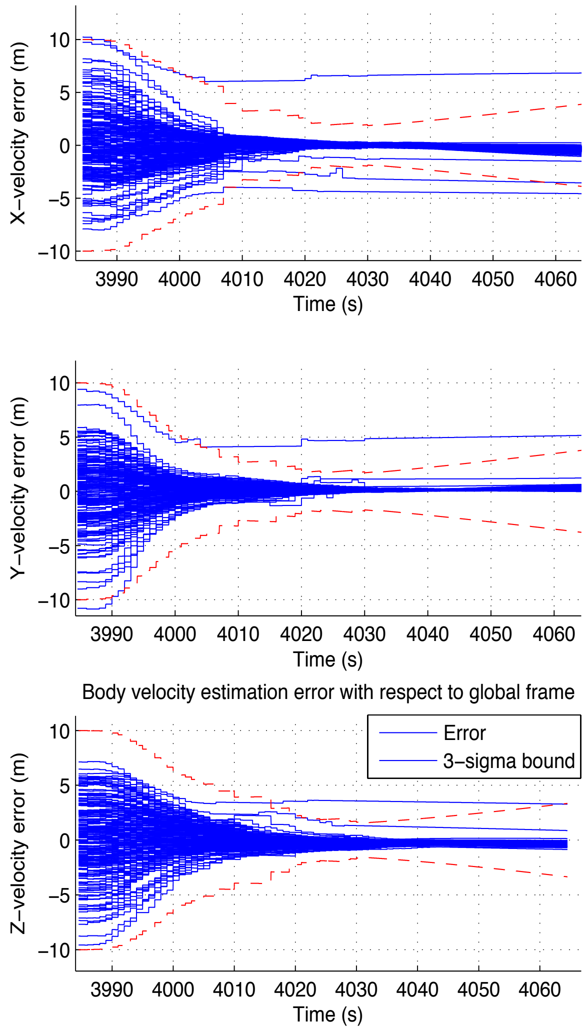
- 200 GHT Monte Carlo runs
  - 3σ initial uncertainty: 1 deg, 10 m/s, 100 m per axis
  - 250 distributed online features
  - 2x4000-features maps (switch at 4005 sec)
    - ➔ Higher-density map for low altitude-matching
  - GHT parameters:
    - 100-pixel neighboorhood zone
    - 10-pixel quantization step
  - 93 % runs converged (filter tuning for the 7% remaining)

Monte Carlo runs

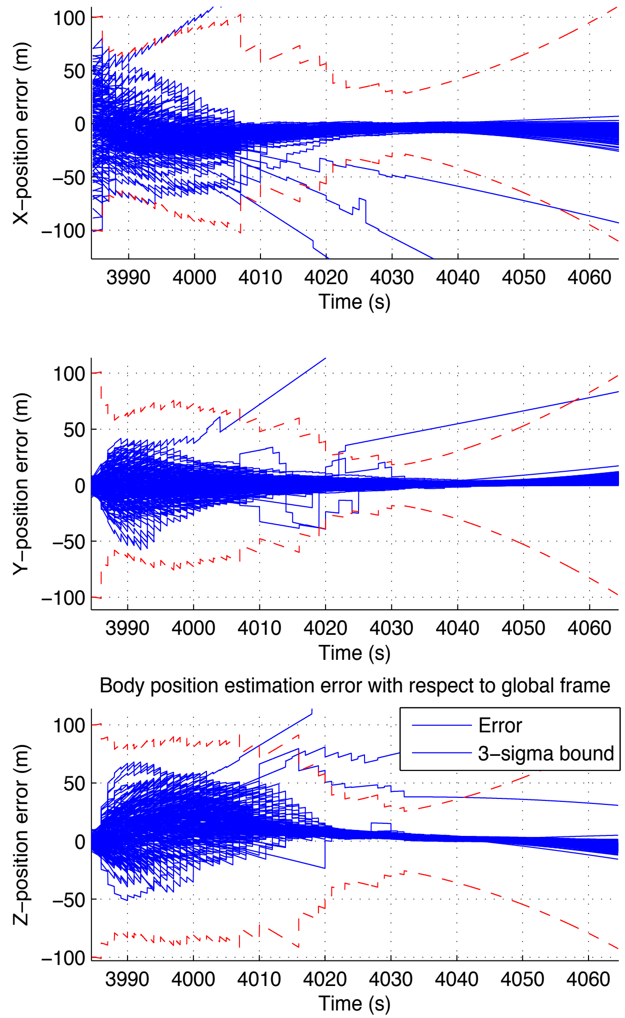
Attitude



Velocity



Position



Monte Carlo results

All runs

Variable	$3\sigma_V$	$3\sigma_{TD}$
Attitude / Yaw (deg)	0.3	0.1
Attitude / Pitch (deg)	0.6	0.3
Attitude / Roll (deg)	0.7	0.4
Velocity / X-axis (m/s)	1.9	2.0
Velocity / Y-axis (m/s)	1.0	1.1
Velocity / Z-axis (m/s)	1.1	0.9
Position / X-axis (m)	78.1	140.5
Position / Y-axis (m)	40.1	74.8
Position / Z-axis (m)	38.9	66.2

93% of the runs

Variable	$3\sigma_V$	$3\sigma_{TD}$
Attitude / Yaw (deg)	0.3	0.1
Attitude / Pitch (deg)	0.6	0.3
Attitude / Roll (deg)	0.6	0.3
Velocity / X-axis (m/s)	0.4	0.6
Velocity / Y-axis (m/s)	0.2	0.4
Velocity / Z-axis (m/s)	0.6	0.3
Position / X-axis (m)	11.3	23.0
Position / Y-axis (m)	4.7	7.1
Position / Z-axis (m)	9.2	10.3

On-going work: decrease the number of diverging runs

➔ Include filter uncertainties in the voting process

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Conclusion

- 2 contributions for geometric mapped landmark matching
  - Generalized Hough Transform yields better results
- Extended Kalman filter structure
  - Processing delays accounted for
- Preliminary validation on a lunar descent sequence at low altitude:
  - Last absolute match at 45 m altitude.
  - Promising to achieve pinpoint landing accuracy or aerial vehicle global navigation.
  - 3D-compatible: no flat world assumption

- Future work:
  - Reduce 7% failures: include filter uncertainties into voting process.
  - Orbit-to-touchdown trajectory, more illuminations, more 3D topographies.
  - Include image scale in feature extraction for repeatability
    - Test extractors taking scale into account: e.g. Harris-Laplace features.
    - Test more specific features: e.g. craters
  - Compare EKF with UKF and PF

Questions?

References: Fischler et al., 1981, *Communications of the ACM*, 24

Pham et al., 2009, in *AIAA Guidance, Navigation and Control*

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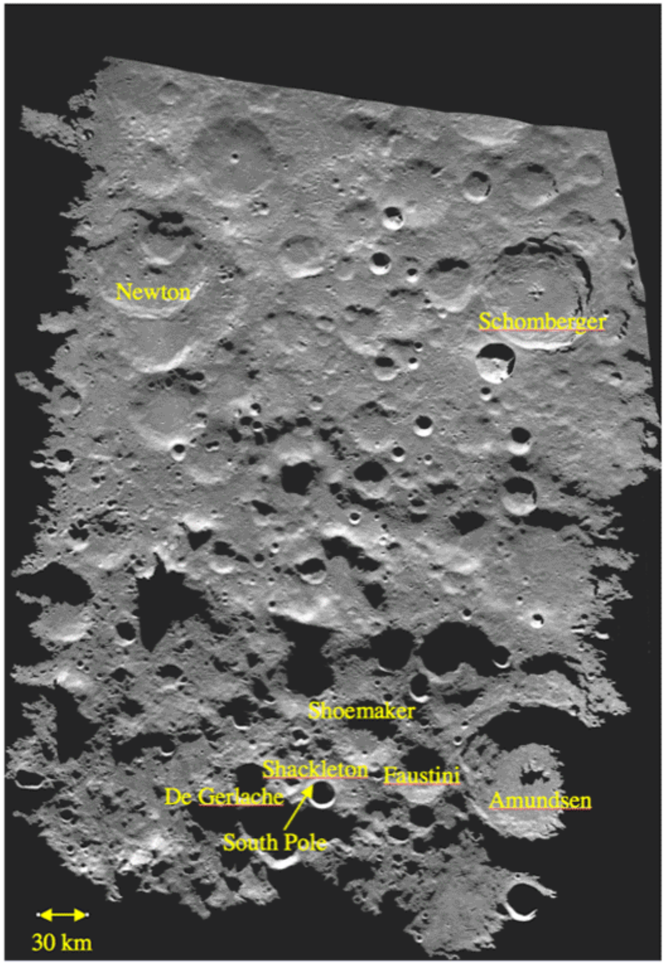
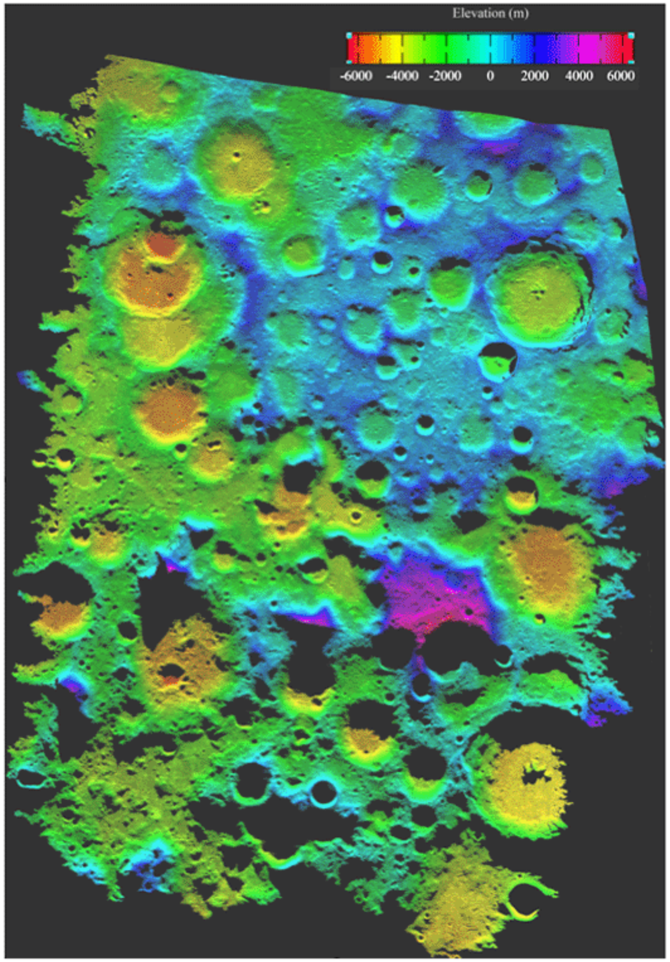
Lunar South Pole Topography



Backscatter image of the lunar south pole region obtained by the GSSR after correcting for the antenna pattern.



Color coded elevation contours overlaid on the the radar backscatter image.

(From Hensley, S.,E. Gurrola, P. Rosen, M. Slade, J. Jao, M. Kobrick, B. Wilson, C. Chen, and R. Jurgens, "An Improved Map of the Lunar South Pole with Earth Based Radar Interferometry." from: RadarCon2008 Special Issue, to be published in IET Radar, Sonar, and Navigation journal.)

Alternatives to EKF?

- Measurement projection function ⇔ highly non-linear
- EKF linearization for Kalman measurement update
  - But important landmark prediction errors for typical planetary landing uncertainties…
  - Measurement noise should be set in tens of pixels instead of a few.

➔ Less efficient measurements ➔ More matched points needed

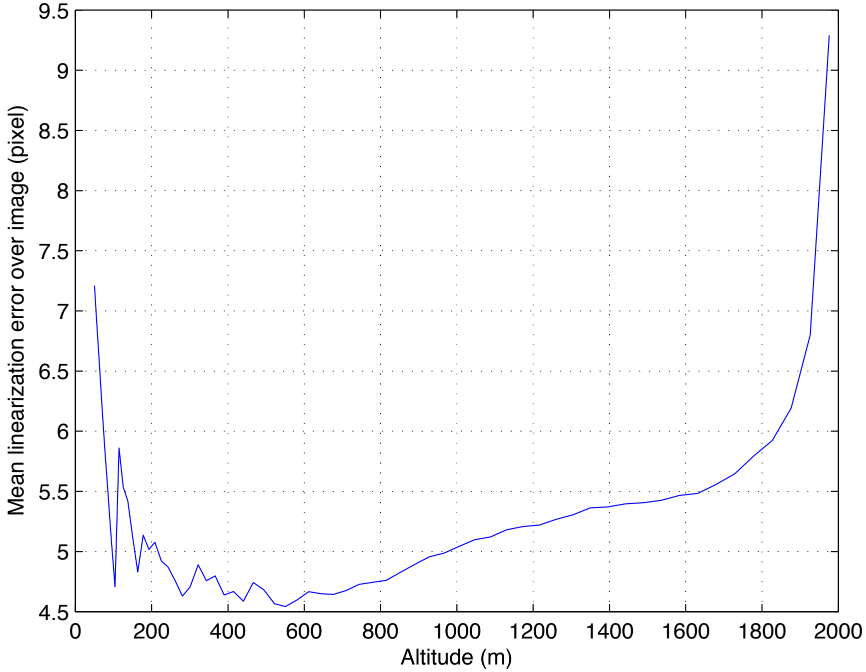


Figure: 1024x1024 image mean linearization error for lunar approach phase

UKF ? PF ?